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# Application of Least Squares Support Vector Machine for Regression to Reliability Analysis

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**Abstract**

In order to deal with the issue of huge computational cost very well in direct numerical simulation, the traditional response surface method (RSM) as a classical regression algorithm is used to approximate a functional relationship between the state variable and basic variables in reliability design. The algorithm has treated successfully some problems of implicit performance function in reliability analysis. However, its theoretical basis of empirical risk minimization narrows its range of applications for the regression model. In contrast to classical algorithms, the support vector machine for regression (SVR) based on structural risk minimization has the excellent abilities of small sample learning and generalization, and superiority over the traditional regression method. Nevertheless, SVR is time consuming and huge space demanding for the reliability analysis of large samples. This article introduces the least squares support vector machine for regression (LSSVR) into reliability analysis to overcome these shortcomings. Numerical results show that the reliability method based on the LSSVR has excellent accuracy and smaller computational cost than the reliability method based on support vector machine (SVM). Thus, it is valuable for the engineering application.

*Keywords:* mechanism design of spacecraft; support vector machine for regression; least squares support vector machine for regression; Monte Carlo method; reliability; implicit performance function

## 1. Introduction

Reliability is an issue of high significance in engineering design, when the variables are conspicuously random[1]. Generally, it is a crucial aspect to get the performance function in reliability analysis. It is very convenient to manage the reliability analysis based on performance function, whereas, the performance function is formulated with an explicit function. However, the performance function is always expressed in implicit function in practical problems. Theoretically, any reliability analysis method based on explicit performance function is also suitable for implicit performance function[1-2]. Yet, due to the unknown performance function, there are still many unconquerable problems in practical treatment, which restrict such as first order reliability method (FORM), second order reliability method (SORM), etc. In order to conquer these problems brought about by implicit function, since 1990s various kinds of regression methods have been constantly used to solve the reliability analysis problem induced by implicit performance function[3]. The classic method is response surface method (RSM)[4-7]. Although a lot of excellent researches have been done to improve the accuracy and adaptability of reliability analysis on the RSM, many problems are still remaining in the practical applications[8]. For example, response surface function can only approximate performance function well around the design points. J. E. Hurtado[3] has explained that the drawback of RSM is owing to its being a rigidly non-adaptive regression technique in the statistical learning perspective. At present, a new kind of regression model—support vector machine (SVM) has been applied to reliability analysis to solve those drawbacks of the traditional regression models.

SVM is a kind of statistical learning method. It comprises support vector machine for classification (SVC) and support vector machine for regression (SVR). C. M. Rocco and J. A. Moreno[9] firstly introduced SVM method into the reliability analysis. J. E. Hurtado and D. A. Alvarez[10] treated reliability analysis as a pattern recognition and adopted SVM in conjunction with stochastic finite element to analyze struc-

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tural reliability. Combing with SVR, H. S. Li and Z. Z. Lu[8] first presented SVR-based FORM (SVR-FORM) and SVR-based Monte Carlo simulation (SVR-MCS) methods.

In the theoretical perspective, SVM is a learning algorithm based on statistical learning theory being suitable for small sample. It transforms the problem of searching for the optimal hyperplane between two classes into the problem of solving the maximal classification margin. The maximal margin problem is actually a quadratic programming (QP) problem subjected to the inequality constraint[11]. In spite of SVM's many advantages, one problem is that the size of the matrix of QP problem is directly proportional to the number of training points, so that the standard QP program package cannot be used even for moderately large data sets[12]. It means that regarding the reliability analysis of large samples, the existing SVM methods are time consuming and huge space demanding. To offset these disadvantages, this article introduces the least square support vector machine for regression (LSSVR) into the reliability analysis and puts forward LSSVR-based MCS (LSSVR-MCS) reliability analysis method, and contrasts the time consumption of standard SVR-MCS with that of LSSVR-MCS.

## 2. SVR

From a certain kind of assumed distribution: $P(\boldsymbol{x}, y)$, $\boldsymbol{x}\in\mathbf{R}^n$, $y\in\mathbf{R}$, the sampling points $\{(\boldsymbol{x}_i, y_i)\}_{i=1,2,\cdots,l}$ are generated. If there is a set of functions that map a point in the space $\mathbf{R}^n$ onto the space $\mathbf{R}$[13-16]:

$$F=\{f(\boldsymbol{x},\boldsymbol{w}),\boldsymbol{w}\in\Lambda\,|\,f:\mathbf{R}^n\rightarrow\mathbf{R}\} \tag{1}$$

where $\Lambda$ is a set of parameters, $\boldsymbol{w}$ an undetermined parameter vector.

Then, the regression subject is to find a function $f\in F$ which makes Eq.(2) shown as below have the lowest expected risk

$$R(f)=\int l(y-f(\boldsymbol{x},\boldsymbol{w}))\mathrm{d}P(\boldsymbol{x},y) \tag{2}$$

where $l(y-f(\boldsymbol{x},\boldsymbol{w}))$ is an error function and defined in SVR as

$$l(y-f(\boldsymbol{x},\boldsymbol{w}))=\max\{0,|y-f(\boldsymbol{x},\boldsymbol{w})|-\varepsilon\} \tag{3}$$

where $\varepsilon>0$. Function $f$ can be determined by the following method.

If sampling points are assumed in a linear relation, then the regression function can be written as

$$f(\boldsymbol{x},\boldsymbol{w})=\boldsymbol{w}\cdot\boldsymbol{x}+b \tag{4}$$

But in most cases, the input sampling points and output sampling points are assumed in a nonlinear relation. For this case, SVR method maps each sampling point by a nonlinear function $\boldsymbol{\varphi}$ onto the higher dimensional space and conducts linear regression in the higher dimensional space, so as to attain the original space nonlinear regression effect. Now the function $f$ is rewritten as

$$f(\boldsymbol{x},\boldsymbol{w})=\boldsymbol{w}\cdot\boldsymbol{\varphi}(\boldsymbol{x})+b \tag{5}$$

Thus, the problem of solving the regression function can be transformed to obtain the following optimized solution

$$\min\frac{1}{2}\|\boldsymbol{w}\|^2 \tag{6}$$

The corresponding constraints are

$$|\boldsymbol{w}\cdot\boldsymbol{\varphi}(\boldsymbol{x}_i)+b-y_i|\le\varepsilon\quad(i=1,2,\cdots,l) \tag{7}$$

Considering the possible errors and introducing two slack variables

$$\xi_i,\xi_i^*\ge 0\quad(i=1,2,\cdots,l)$$

the optimization function is then as follows

$$\min\frac{1}{2}\|\boldsymbol{w}\|^2+\gamma\sum_{i=1}^{l}(\xi_i+\xi_i^*) \tag{8}$$

The corresponding constraints are

$$\left.\begin{aligned}&\boldsymbol{w}\cdot\boldsymbol{\varphi}(\boldsymbol{x}_i)+b-y_i\le\xi_i^*+\varepsilon\\&y_i-\boldsymbol{w}\cdot\boldsymbol{\varphi}(\boldsymbol{x}_i)-b\le\xi_i+\varepsilon\\&\xi_i,\xi_i^*\ge 0\\&(i=1,2,\cdots,l)\end{aligned}\right\} \tag{9}$$

For obtaining the solution of this QP, the Lagrange function is introduced

$$\begin{aligned}L(\boldsymbol{w},b,\boldsymbol{\alpha},\boldsymbol{\alpha}^*)=&\frac{1}{2}\|\boldsymbol{w}\|^2+\gamma\sum_{i=1}^{l}(\xi_i+\xi_i^*)-\\&\sum_{i=1}^{l}\alpha_i(\xi_i+\varepsilon-y_i+\boldsymbol{w}\cdot\boldsymbol{\varphi}(\boldsymbol{x}_i)+b)-\\&\sum_{i=1}^{l}\alpha_i^*(\xi_i^*+\varepsilon+y_i-\boldsymbol{w}\cdot\boldsymbol{\varphi}(\boldsymbol{x}_i)-b)-\\&\sum_{i=1}^{l}\eta_i(\xi_i+\xi_i^*)\end{aligned} \tag{10}$$

where $\alpha_i,\alpha_i^*\ge 0\ (i=1,2,\cdots,l)$.

In the optimization process, the inner product calculation in the higher dimensional space is always involved. Using a kernel function $\psi(\boldsymbol{x}_i,\boldsymbol{x}_j)$ to replace the inner product $\boldsymbol{\varphi}(\boldsymbol{x}_i)\cdot\boldsymbol{\varphi}(\boldsymbol{x}_j)$, the Lagrange duality problem is expressed as

$$\begin{aligned}\min_{\boldsymbol{\alpha},\boldsymbol{\alpha}^*}[&\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i^*-\alpha_i)(\alpha_j^*-\alpha_j)\psi(\boldsymbol{x}_i,\boldsymbol{x}_j)+\\&\varepsilon\sum_{i=1}^{l}(\alpha_i^*-\alpha_i)-\sum_{i=1}^{l}y_i(\alpha_i^*-\alpha_i)]\end{aligned} \tag{11}$$

subjected to the constraints

$$\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)=0 \quad (0\le\alpha_i^*,\alpha_i\le\gamma;\ i=1,2,\cdots,l) \tag{12}$$

After getting the optimized solution $\bar{\alpha}$, $\bar{\alpha}^*$, and $\bar{b}$, the regression estimating function is as follows

$$f(\boldsymbol{x})=\sum_{\boldsymbol{x}_i\in\mathrm{SV}}(\bar{\alpha}_i-\bar{\alpha}_i^*)\psi(\boldsymbol{x},\boldsymbol{x}_i)+\bar{b} \tag{13}$$

where SV is a set of support vector for a given sample set.

## 3. LSSVR

The algorithm of the LSSVR is to solve the following optimization question[11,17]

$$\min_{\boldsymbol{w},\boldsymbol{e}} J(\boldsymbol{w},\boldsymbol{e})=\frac{1}{2}\boldsymbol{w}^{\mathrm{T}}\boldsymbol{w}+\gamma\sum_{i=1}^{l}e_i^2 \tag{14}$$

whereas, satisfying the equality constraints

$$y_i=\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\varphi}(\boldsymbol{x}_i)+b+e_i \quad (i=1,2,\cdots,l) \tag{15}$$

The polynomial of Lagrange duality problem is

$$L(\boldsymbol{w},b,\boldsymbol{e},\boldsymbol{\alpha})=J(\boldsymbol{w},\boldsymbol{e})-\sum_{i=1}^{l}\alpha_i(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\varphi}(\boldsymbol{x}_i)+b+e_i-y_i) \tag{16}$$

Its optimization conditions are

$$\left.\begin{aligned}
&\frac{\partial L}{\partial \boldsymbol{w}}=\boldsymbol{0}\to\boldsymbol{w}=\sum_{i=1}^{l}\alpha_i\boldsymbol{\varphi}(\boldsymbol{x}_i)\\
&\frac{\partial L}{\partial b}=0\to-\sum_{i=1}^{l}\alpha_i=0\\
&\frac{\partial L}{\partial e_i}=0\to\alpha_i=\gamma e_i\\
&\frac{\partial L}{\partial \alpha_i}=0\to\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\varphi}(\boldsymbol{x}_i)+b+e_i-y_i=0\\
&(i=1,2,\cdots,l)
\end{aligned}\right\} \tag{17}$$

Eq.(17) can also be written as the following linear equations set

$$\begin{bmatrix}\boldsymbol{I}&\boldsymbol{0}&\boldsymbol{0}&-\boldsymbol{Z}^{\mathrm{T}}\\ \boldsymbol{0}&\boldsymbol{0}&\boldsymbol{0}&-\boldsymbol{1}^{\mathrm{T}}\\ \boldsymbol{0}&\boldsymbol{0}&\gamma\boldsymbol{I}&-\boldsymbol{I}\\ \boldsymbol{Z}&\boldsymbol{1}&\boldsymbol{I}&\boldsymbol{0}\end{bmatrix}\begin{bmatrix}\boldsymbol{w}\\ b\\ \boldsymbol{e}\\ \boldsymbol{\alpha}\end{bmatrix}=\begin{bmatrix}\boldsymbol{0}\\ \boldsymbol{0}\\ \boldsymbol{0}\\ \boldsymbol{y}\end{bmatrix} \tag{18}$$

where

$$\boldsymbol{e}=[e_1\ \ e_2\ \ \cdots\ \ e_l]^{\mathrm{T}}$$
$$\boldsymbol{y}=[y_1\ \ y_2\ \ \cdots\ \ y_l]^{\mathrm{T}}$$
$$\boldsymbol{1}=[1\ \ 1\ \ \cdots\ \ 1]^{\mathrm{T}}$$
$$\boldsymbol{\alpha}=[\alpha_1\ \ \alpha_2\ \ \cdots\ \ \alpha_l]^{\mathrm{T}}$$
$$\boldsymbol{Z}=[\boldsymbol{\varphi}(\boldsymbol{x}_1)\ \ \boldsymbol{\varphi}(\boldsymbol{x}_2)\ \ \cdots\ \ \boldsymbol{\varphi}(\boldsymbol{x}_l)]^{\mathrm{T}}$$

By eliminating $\boldsymbol{e}$ and $\boldsymbol{w}$, and utilizing the following Mercer condition,

$$\varOmega_{kj}=(\boldsymbol{\varphi}(\boldsymbol{x}_k))^{\mathrm{T}}\boldsymbol{\varphi}(\boldsymbol{x}_j)=\psi(\boldsymbol{x}_k,\boldsymbol{x}_j) \quad (k,j=1,2,\cdots,l) \tag{19}$$

the resultant equations set is then only related to $\boldsymbol{\alpha}$ and $b$. Therefore, Eq.(18) is transformed into

$$\begin{bmatrix}\boldsymbol{0}&\boldsymbol{1}^{\mathrm{T}}\\ \boldsymbol{1}&\boldsymbol{\varOmega}+\gamma^{-1}\boldsymbol{I}\end{bmatrix}\begin{bmatrix}b\\ \boldsymbol{\alpha}\end{bmatrix}=\begin{bmatrix}\boldsymbol{0}\\ \boldsymbol{y}\end{bmatrix} \tag{20}$$

On the assumption that $\boldsymbol{A}=\boldsymbol{\varOmega}+\gamma^{-1}\boldsymbol{I}$ and because $\boldsymbol{A}$ is a symmetric and positive semi-definite matrix, $\boldsymbol{A}^{-1}$ does exist. Thus, the solution of Eq.(20) can be formulated as

$$\left.\begin{aligned}
&b=\frac{\boldsymbol{1}^{\mathrm{T}}\boldsymbol{A}^{-1}\boldsymbol{y}}{\boldsymbol{1}^{\mathrm{T}}\boldsymbol{A}^{-1}\boldsymbol{1}}\\
&\boldsymbol{\alpha}=\boldsymbol{A}^{-1}(\boldsymbol{y}-b\boldsymbol{1})
\end{aligned}\right\} \tag{21}$$

Using the first equation of Eq.(17) to replace the $\boldsymbol{w}$ in Eq.(5) and using Eq.(19), the desired regression function can be written as

$$f(\boldsymbol{x})=\sum_{i=1}^{l}\alpha_i\psi(\boldsymbol{x},\boldsymbol{x}_i)+b \tag{22}$$

where $\alpha_i$ and $b$ are the solutions of Eq.(21).

## 4. Numerical Examples

In this section, the reliability method is adopted which is based on LSSVR-MCS method. In the reliability analysis, it is mainly using LSSVR to create a surrogate model of physical performance function. From the method provided by Ref.[8], the sampling points are selected randomly according to the distribution of the random variables and then introduced into the ready-made LSSVR surrogate model to get the response values. The failure probability can be calculated by

$$P_{\mathrm{f}}=P(g(\boldsymbol{x})\le 0)\approx P(f(\boldsymbol{x})\le 0)\approx\frac{N_{\mathrm{f}}}{N} \tag{23}$$

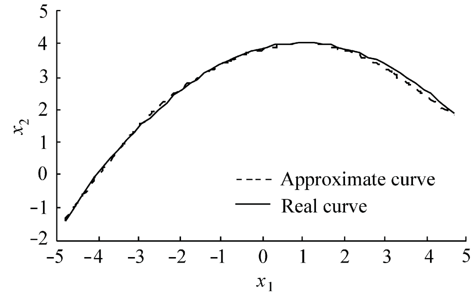
where $g(\boldsymbol{x})$ is physical performance function, $f(\boldsymbol{x})$ surrogate function created by LSSVR, $N$ the total sampling number according to the random variable probability density and 10 000 random samples are taken, and $N_{\mathrm{f}}$ the number of sampling points within the zone of $f(\boldsymbol{x})\le 0$.

**Example 1** Quadratic limit state reliability analysis

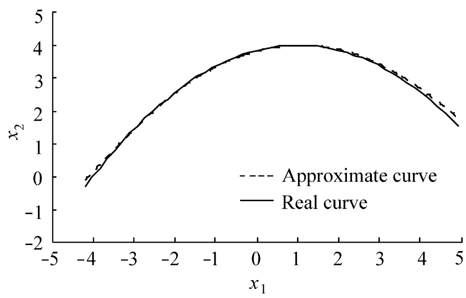
Eq.(24) is a quadratic limit state function (LSF) and is often taken to examine the accuracy of the implicit limit state reliability analysis method[7-8].

$$g(\boldsymbol{x})=4-\frac{4}{25}(x_1-1)^2-x_2 \tag{24}$$

where $x_1$ and $x_2$ obey the standard normal distribution. The comparison between the approximate curves and the real curves of LSF are shown in Fig.1. The approximate curves are obtained on the basis of SVR and LSSVR respectively and only twenty samples are chosen as training points. Two hundred of the samples are taken into account as a large sample case and the corresponding figures are shown in Fig.2. The results of failure probability and computation cost for different number of samples and methods are summarized in Table 1.

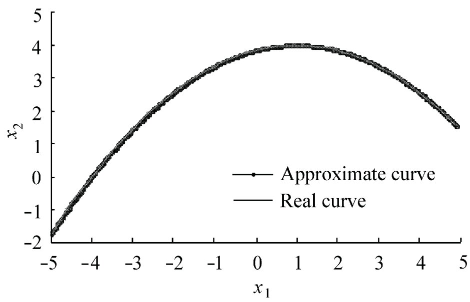



(a) SVR

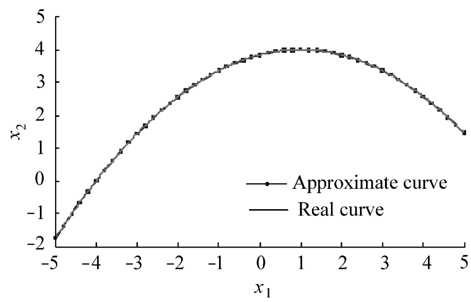



(b) LSSVR

Fig.1 Comparison of real and approximate curves of LSF for small sample (Example 1).




(a) SVR




(b) LSSVR

Fig.2 Comparison of real and approximate curves of LSF for large sample (Example 1).

**Table 1 Comparison of results (Example 1)**

| | Small sample | | |
|---|---|---|---|
| | MCS | SVR-MCS | LSSVR-MCS |
| Failure probability/$10^{-4}$ | 8.0 | 8.0 | 8.0 |
| Learning time/s | | 0.282 | 0.016 |
| Total time/s | | 6.407 | 1.656 |
| | Large sample | | |
| | MCS | SVR-MCS | LSSVR-MCS |
| Failure probability/$10^{-4}$ | 8.0 | 8.0 | 8.0 |
| Learning time/s | | 69.016 | 0.484 |
| Total time/s | | 130.250 | 12.922 |

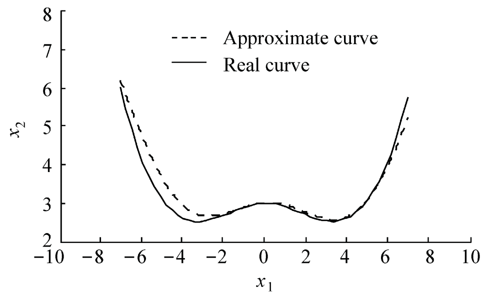
**Example 2** Quartic limit state reliability analysis

For general purpose, Eq.(25) shows a quartic LSF

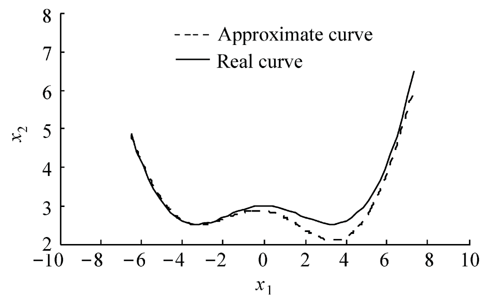
$$g(\boldsymbol{x}) = 2 + \exp(-\frac{x_1^2}{10}) + (\frac{x_1}{5})^4 - x_2 \tag{25}$$

where $x_1$ and $x_2$ are standard normal distribution variables. The comparison of real and approximate curves of LSF for both SVR and LSSVR are demonstrated in Fig.3 corresponding to the case of a small samples. The corresponding figures for a large sample are shown in Fig.4.

In case of Example 2, the results of failure probability and computation cost are listed in Table 2 for different sample sizes and different methods, respectively.

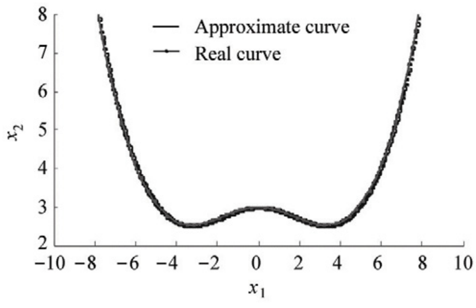



(a) SVR

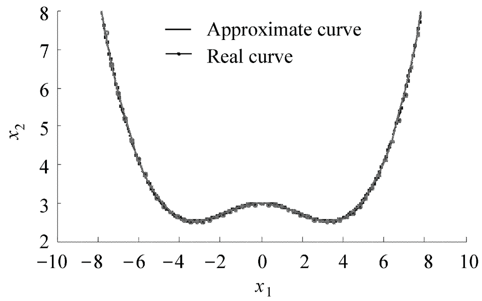



(b) LSSVR

Fig.3 Comparison of real and approximate curves of LSF for small sample (Example 2).



(a) SVR



(b) LSSVR

Fig.4 Comparison of real and approximate curves of LSF for large sample (Example 2).

**Table 2 Comparison of results (Example 2)**

| | Small sample | | |
|---|---|---|---|
| | MCS | SVR-MCS | LSSVR-MCS |
| Failure probability/$10^{-3}$ | 1.84 | 1.80 | 1.80 |
| Learning time/s | | 0.297 | 0.016 |
| Total time/s | | 6.484 | 1.703 |
| | Large sample | | |
| | MCS | SVR-MCS | LSSVR-MCS |
| Failure probability/$10^{-3}$ | 1.84 | 1.80 | 1.80 |
| Learning time/s | | 75.531 | 0.469 |
| Total time/s | | 136.047 | 12.907 |

**Example 3** Reliability analysis of three-span continuous beam

The result of reliability analysis for three-span beam is presented in Ref.[18]. Its LSF is

$$g(q,E,I)=\frac{L}{360}-0.006\,9\frac{qL^4}{EI} \tag{26}$$

where $q$ denotes the distributed loads, $E$ the modulus of elasticity, and $I$ the moment of inertia. These variables are distributed normally and independent of each other, and their distribution parameters are given in Table 3. In order to highlight the distinction of computation cost between SVR-MCS and LSSVR-MCS, five hundred of the samples are chosen as training samples. Table 4 lists the comparison of results derived from LSSVR-MCS and SVR-MCS.

**Table 3 Distribution parameters of variables (Example 3)**

| Random variable | Mean | Standard deviation |
|---|---|---|
| $q$/(kN·m$^{-1}$) | 10 | 0.4 |
| $E$/($10^7$kN·m$^{-2}$) | 2 | 0.5 |
| $I$/($10^{-4}$ m$^4$) | 8 | 1.5 |

**Table 4 Comparison of results for large sample (Example 3)**

| | MCS | SVR-MCS | LSSVR-MCS |
|---|---|---|---|
| Failure probability/$10^{-4}$ | 8.96 | 9.00 | 9.00 |
| Learning time/s | | 1 140.352 | 4.125 |
| Total time/s | | 1 287.875 | 29.188 |

**Example 4** Reliability analysis of deployable mechanism for huge space station

The deployable mechanism for huge space station is an important object in the research and development of space vehicles. It is a planar flexible multibody system. Figs.5-6 are the initial state and deployable state of this mechanism, respectively.

The flexible deployable mechanism is static in initial state. It takes 30 s to start the initial state and transmit to the end. From 0 s to 10 s, the mechanism is driven by a momentum $M_d$ and then the mechanism completes the rest of the process by inertia. The resistant momentum $M_f$ and assembling error (showed by the coordinates $x_p$ and $y_p$) are taken into account during the dynamic simulation. L. C. Yu[19] pointed out that the maximum horizontal velocity of component $B_5$ is less than 60 mm/s in order to avoid coupling vibration in the deploying process. The flexible model of the mechanism is established using virtual prototyping software ADAMS. The variables listed in Table 5 are assumed to be normal distribution and the maximum horizontal velocity of component $B_5$ is chosen as the design objective during the numerical simulation. It takes around 2 min to accomplish the simulation of one group of samples by a computer with CPU 2GHz/

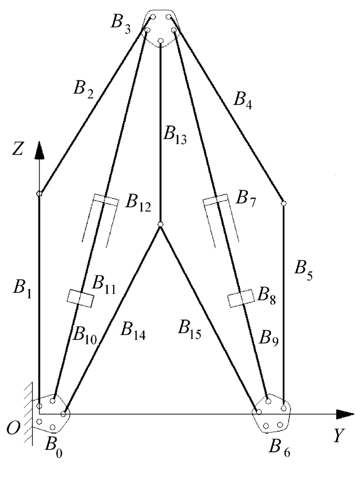


Fig.5 Initial state of a deployable mechanism[19].

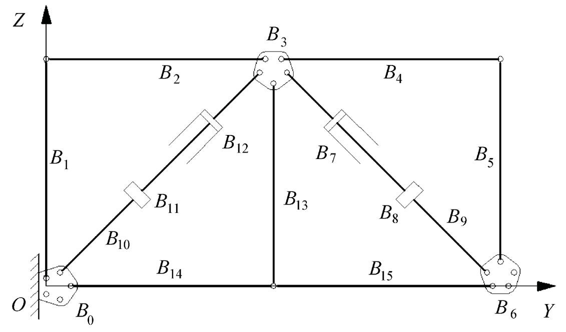



Fig.6 Deployable state of a deployable mechanism[19].

2G and 3 h are required to accomplish the simulation of 100 samples. Therefore, it is a time consuming method to apply MCS method directly to the mechanical reliability analysis when large samples are needed. One hundred groups of samples derived from ADMAS simulation are taken as the training samples of SVR and LSSVR to create the surrogate models of the deployable mechanism. The results based on different methods are listed in Table 6.

**Table 5 Distribution parameters of variables (Example 4)**

| Random variable | Mean | Deviation |
|---|---|---|
| $M_d$ | –4.0 N·mm | 0.1 (N·mm)$^2$ |
| $M_f$ | 0.5 N·mm | 0.025 (N·mm)$^2$ |
| $t$ | 10 s | 0.25 s$^2$ |
| $x_p$ | –246.858 mm | 4 mm$^2$ |
| $y_p$ | 643.209 mm | 4 mm$^2$ |

**Table 6 Comparison of results (Example 4)**

| | SVR-MCS | LSSVR-MCS |
|---|---|---|
| Failure probability | 0.045 5 | 0.046 5 |
| Learning time/s | 8.997 8 | 0.149 1 |
| Total time/s | 39.656 | 5.575 |

The results obtained from LSSVR-MCS and SVR-MCS are nearly the same as that given by L. C. Yu in Ref.[19], in which the failure probabilities based on MCS and artificial netural network-based Monte Carlo simulation (ANN-MCS) are 0.046 3 and 0.045 0, respectively.

## 5. Conclusions

This article puts forward a revised reliability analysis based on SVM, namely LSSVR-MCS method. The LSSVR-MCS method transforms the inequality constraint of SVR-MCS into equality constraint so as to change the solving algorithm of the support vector machine from quadratic programming to a linear equation set and make the solving approach easier. The numerical results indicate:

(1) With the increase of number of training samples, the approximate LSF curve approaches the real one more closely.

(2) Whatever the computation cost, failure probability or approximate curve, the results obtained from LSSVR-MCS are as good as that obtained from SVR-MCS for small sample.

(3) In the case of large sample, LSSVR-MCS method is obviously superior to SVR-MCS method in computation cost.

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CALL FOR PAPERS

# The 3rd International Basic Research Conference on Rotorcraft Technology

A third conference will be held in celebration of the 24th anniversary of the first conference at the same university, Nanjing University of Aeronautics and Astronautics in 1985.

## Nanjing, China, Nov. 9 - 11, 2009

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The American Helicopter Society, the Pennsylvania State University
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### *Subject matter/scope/conference theme:*

A comprehensive array of advanced rotorcraft basic research technologies will be emphasized, including RUAV (Rotary Unmanned Air Vehicles) and MAV (Micro Air Vehicles). Interdisciplinary technologies in the areas of rotorcraft aerodynamics, dynamics & vibration, acoustics, flight controls, HUMS, structures, propulsion and drive systems, ice protection, and avionics will be covered. The reported work will include analytical capabilities, new experimental studies, new vehicle design concepts, and correlation/validation efforts. Analytical papers may range from basic aerodynamics, including low Reynolds numbers, to results of comprehensive analysis programs. Experimental papers will span model- to full-scale wind tunnel and flight test programs. Revolutionary new rotorcraft concepts or applications of emerging technologies to new rotorcraft missions will be addressed.

### *Abstract Submittal:*

Abstracts should be written in English and should be no longer than five papers, including background, approach, key results, conclusions, and sample supporting figures.
The approach and results should be presented in sufficient detail to allow the reviewer to determine the quality, scope, significance and current status of the work that will be described in the final paper. Priority will be given to papers in which significant results and conclusions are provided. Submit abstracts, including paper title, author(s), name(s), address, phone, fax and e-mail address no later than *May 30, 2009*. Electronic submittal is strongly preferred.

### *Completed Papers:*

Authors will be notified of final selection by *June 30, 2009*. Presentations will be given in an open forum and all papers will be published in the conference proceedings. Final papers are due *August 31, 2009*, preferably in electronic format. The author is responsible for any necessary clearances and approvals.

All questions should be directed to the Technical Chairman: Prof. GAO Zheng, NUAA, gaoae@nuaa.edu.cn, 86-25-84892120, and Prof. Ken Brentner, Penn State University, AHS Journal Editor-in-Chief, (814)865-7092, Ksbrentner@psu.edu, or to the Arrangements Chairman: Prof. XIA Pinqi, NUAA, xiapq@nuaa.edu.cn, 86-25-84892491.

Abstracts should be submitted to Prof. Edward Smith, Penn State, ecs5@psu.edu,
or to Prof. XIA Pinqi, NUAA, xiapq@nuaa.edu.cn